Transfer Learning Approach to Enhance a Student Attendance System Through Fingerprint Recognition

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Abstract. This study investigates a new transfer learning approach designed to improve the accuracy and efficiency of a student attendance system using advanced fingerprint recognition methods. By employing pre-trained models such as the Xception and InceptionResNetV2 architectures, the research highlights the significant benefits of transfer learning in enhancing fingerprint-based student identification. The method strategically utilizes data augmentation techniques to address challenges related to limited dataset sizes, ensuring robust validation and improved scalability. The evaluation of the approach encompasses various performance metrics, including accuracy, precision, recall, F1 score, and MCC, providing a comprehensive understanding of its effectiveness. Achieving a 100% accuracy rate in fingerprint recognition underscores the reliability and practical feasibility of the transfer learning approach in student attendance systems. This study offers valuable insights into the intersection of biometrics and educational technology, facilitating the development of precise attendance tracking systems with broader applications in educational environments. The success of the proposed approach suggests promising opportunities for further research and development, indicating a positive trajectory for improving student-focused technological solutions.

Keywords: Transfer Learning · Student Attendance System · Fingerprint Recognition · Educational Technology.

1 INTRODUCTION

Student identification using fingerprint technology is a cutting-edge approach that harnesses the unique biometric characteristics of an individual's fingerprints for accurate and secure authentication. In this innovative method, each student's distinct fingerprint pattern serves as a reliable means of identification, offering a level of precision unmatched by traditional methods. This approach not only enhances security measures within educational institutions but also streamlines administrative processes, particularly in the realm of attendance tracking. By

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deploying fingerprint recognition systems, schools and universities can automate the identification process, making it both efficient and resistant to potential fraud. Moreover, the use of fingerprint technology provides a non-intrusive and user-friendly experience for students, as the authentication process simply requires a quick scan of their fingerprints. As technology continues to advance, student identification through fingerprints represents a sophisticated and practical solution that aligns with the evolving needs of educational environments, ensuring a seamless integration of modern technology into daily administrative tasks.

A student attendance system employing a transfer learning approach represents a sophisticated and innovative paradigm in the realm of educational technology[1]. Transfer learning [2], a technique where knowledge gained from one task is applied to improve the performance of a different but related task, is harnessed to enhance the accuracy and efficiency of student attendance tracking. In this context, pre-trained models are utilized to leverage existing knowledge and patterns, making the system adaptable and capable of learning from diverse datasets. The transfer learning approach enables the attendance system to better handle variations in student appearances and environmental conditions, ensuring robust performance. By leveraging knowledge acquired from prior tasks, the system becomes adept at recognizing attendance patterns, thereby reducing the need for extensive training on domain-specific data. This not only expedites the implementation process but also facilitates the system's adaptability to different educational environments. As educational institutions strive for technological advancements, a student attendance system employing transfer learning emerges as a forward-thinking solution that combines the power of machine learning with the practical demands of tracking student attendance accurately and efficiently [3].

This study contributes by applying fingerprint recognition technology to the context of monitoring student attendance. This involves using biometric data to uniquely identify students based on their fingerprints.

The incorporation of transfer learning in this study is a significant contribution. Transfer learning involves leveraging pre-trained models to improve the performance of a specific task, in this case, fingerprint recognition for attendance monitoring. This approach could potentially enhance accuracy and efficiency.

This research employs the Xception [4] and InceptionResNetV2 [5] architectures for fingerprint recognition in student attendance. The innovations and contributions of our study are detailed as follows:

- Implementation of transfer learning techniques within the domain of student attendance systems by leveraging pre-existing models like Xception and InceptionResNetV2.
- Data augmentation techniques are employed to address the scarcity of dataset images, ensuring robust validation for the proposed approach.
- The validation process of the proposed method involves a thorough examination of various performance metrics, including Accuracy Score, Precision Score, Recall Score, F1 Score, and MCC.

– The results showcase remarkable performance, with an impressive 100% accuracy rate in fingerprint recognition for student attendance.

The remainder of this document is structured as follows: section ii provides an overview of previous works related to fingerprint recognition and the transfer learning approach, while section iii describes the materials and methods used in this work. Section iv presents detailed experimental results, and section v provides a comparative analysis of the proposed models. Lastly, section vi concludes the paper.

2 Related work

Integrating biometric systems into student attendance management signifies a considerable advancement over traditional methods. Our study explores various methodologies that have laid the groundwork for this progress. This section reviews the relevant literature, scrutinizing prior efforts that have utilized transfer learning techniques for biometric identification, with a particular focus on fingerprint recognition.

Ennajar and Bouarifi, [3] utilized a Deep Transfer Learning Approach for the Student Attendance System amid the COVID-19 Pandemic. They employed six pre-trained convolutional neural networks (CNNs) to create a masked face recognition model. A dataset comprising faces with masks was generated and employed to evaluate the performance of the six CNN models, emphasizing the augmentation of training samples to improve model proficiency. The research findings underscore the efficacy of pre-trained models, particularly Xception and InceptionResNetV2, in precisely detecting faces with masks while necessitating minimal training time. The six pre-trained networks employed in this investigation encompassed Xception, InceptionResNetV2, MobileNetV2, DenseNet, ResNet101V2, and EfficientNetB0, achieving validation accuracy of 96.75%, 96.50%, 88.60%, 95.28%, 90.94%, and 88.70%, respectively.

Do and Tran-Nguyen, [6] were involved in collecting real datasets of fingerprint images from students at Can Tho University and training popular deep networks such as VGG, ResNet50, Inception-v3, and Xception on a training dataset. The trained models were then used for feature extraction, with only the last layer fine-tuned for new fingerprint image datasets. The empirical test results on three different fingerprint image datasets (FP-235, FP-389, FP-559) demonstrate that the deep network models achieve high accuracy, with ResNet50 models reaching classification accuracy of 99.00%, 98.33%, and 98.05% on FP-235, FP-389, and FP-559, respectively.

Mohammed et al. [7] proposed a fingerprint-based attendance system designed to improve attendance tracking in educational institutions. Replacing traditional manual attendance methods with biometric technology, this system enhances efficiency and accuracy, reduces time wastage, and prevents fraudulent attendance marking. It offers cost-effective, flexible integration with existing infrastructure and provides real-time attendance monitoring that is accessible to guardians online.

Lamin et al. [8] introduced a student attendance system incorporating fingerprint biometrics. In this system, students are obligated to submit their thumbprints using the installed fingerprint device in the classroom to record attendance. The device captures fingerprint images, which are subsequently stored on the server to facilitate the attendance process.

Walhazi et al. [9] proposed a novel framework for automatically classifying fingerprints. This system employs a combination of deep transfer learning models and a majority voting system, aiming to classify six different types of fingerprints using 16 commonly used deep transfer learning models trained on fingerprint datasets. The key finding is that a combination of three specific models—DenseNet 121, ResNet152V1, and EfficientNetB7—achieves higher precision in fingerprint classification compared to individual models. This suggests potential for enhanced performance in biometric systems, especially in areas such as forensic investigations, law enforcement, and security.

Kute et al. [10] suggested a novel framework for face recognition using fingerprints through transfer learning and Bregman divergence-based regularization. The proposed method aims to establish a common subspace where the characteristics of both fingerprints and face images can be effectively matched, despite their inherent differences in data distribution and domain. By integrating various dimensionality reduction algorithms (such as PCA, FLDA, and DLA) with the regularization technique, the framework seeks to enhance the precision of biometric recognition systems, particularly in forensic applications. The experimental results demonstrate the effectiveness of this method in improving the accuracy of identifying individuals based on their biometric data, suggesting its potential utility in security and forensic investigations.

Verma and Gupta [11] proposed a fingerprint-based student attendance system that incorporates a GSM module to enhance traditional methods of tracking attendance. The system employs a microcontroller interfaced with a fingerprint sensor and a GSM module for real-time monitoring of attendance. It is designed to automatically record student attendance and relay this information to guardians or authorized personnel via GSM.

Abdullateef et al. [12] proposed a fingerprint-based student attendance management system that incorporates automatic Excel computation. This system addresses the challenges of manual attendance methods by utilizing a mathematical model and block diagram representation in its design. Employing Proteus software for simulation and CoolTerm software alongside Excel for implementation, it demonstrated high accuracy and reliability in tests involving 15 students. The system achieved a 0% False Acceptance Rate (FAR), 100% True Acceptance Rate (TAR), and 0% False Rejection Rate (FRR), proving to be a secure, credible, and error-free solution compared to manual methods.

Ezema et al. [13] proposed a reliable, secure, fast, and efficient fingerprint-based attendance management system. Designed to replace manual and unreliable methods of tracking attendance, this system has the potential to revolutionize attendance management in academic institutions and other settings. Utilizing fingerprint recognition technology, the system offers a more accurate and fraud-resistant method of recording attendance. It saves time, reduces administrative workload, and eliminates the need for traditional stationery materials.

3 Materials and Methods

3.1 Dataset

The CASIA Fingerprint Database, commonly known as CASIA Fingerprint v5.0 [14], stands out as one of the extensive fingerprint databases, having gathered data from 500 subjects and comprising a total of 20,000 images. This publicly available fingerprint database can be accessed via the official CASIA website [14]. For our research, we utilized a dataset derived from CASIA Fingerprint V5, containing 10,380 fingerprint images distributed across 10 classes, as depicted in Figure 1. Evaluation of the validation and test sets involved new databases with 1247 and 2071 images, respectively. Figure 2 visually represents the configuration of this dataset.

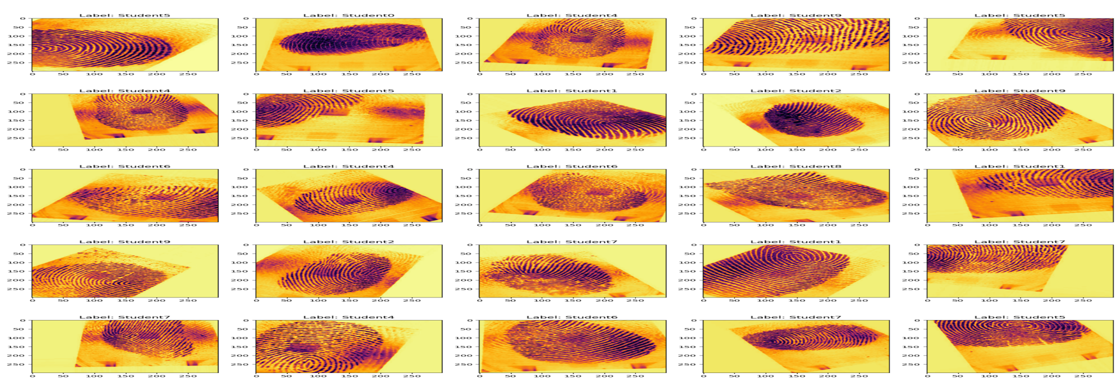


Fig. 1. Example of Fingerprint images in the Fingerprint Dataset

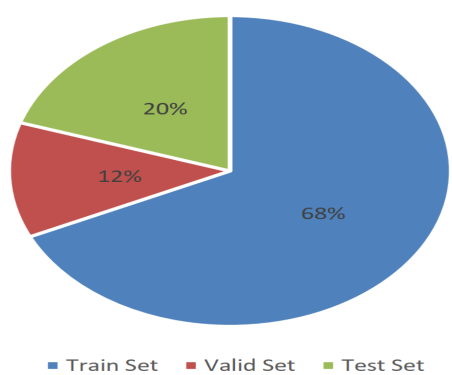


Fig. 2. Distribution of the Fingerprint dataset

3.2 Data augmentation technique

To enhance the performance of the model, we implemented data augmentation techniques. These methods included altering the original images to generate additional variations. In our research, data augmentation was executed to encompass a wider range of scenarios and appearance variations. Diverse transformations, including rotation, scaling, flipping, and adjustments in lighting conditions, were applied to the images. The primary goal of augmenting the dataset was to enhance its diversity, enabling the model to generalize more effectively and handle various real-world scenarios. The specific parameters chosen for each operation are outlined in Table 1.

Table 1. Data augmentation parameters.

Operations	Values
Rotation	30 degrees
Shearing	0.2 radians
Zooming (range)	0.2
Horizontal flip	True
Vertical flip	True
Brightness	[0.4, 1.5]

3.3 Parameters Settings

Table 2 provides detailed settings for the parameters used in configuring the Xception and InceptionResNetV2 models. The data split between training, testing, and validation is set at 70:22:10, respectively. The models use an input shape of 299×299×3 for processing images. A learning rate of 0.0001 is applied, utilizing the Adam optimizer to enhance the training efficiency. The activation function employed is SoftMax, suitable for multi-class classification tasks. Additionally, these settings are tested and validated using a dataset comprising 10 students. This configuration aims to optimize the model's performance for precise outcomes.

Table 2. Parameters settings of Xception and Inceptionresnetv2 models.

Parameters	Values
Train,Test and val Split	70:22:10
Input shape	(299,299,3)
Learning Rate	0.0001
optimizer	Adam
Activation	SoftMax
Number of students	10

4 Results and discussions

4.1 Evaluation Metrics

In our study, the performance of the transfer learning approach in the context of student fingerprint recognition was evaluated using a comprehensive set of metrics. The primary metric, accuracy, provided an overarching measure of the model's ability to correctly identify student fingerprints. Precision was scrutinized to assess the accuracy of identifications, ensuring the system reliably recognized genuine fingerprints. The recall was significant for evaluating the model's sensitivity, emphasizing its capability to correctly identify all relevant fingerprints. The F1 score, a balanced metric, offered a nuanced understanding by considering both precision and recall. Receiver Operating Characteristic (ROC) curves and the associated Area Under the Curve (AUC-ROC) were employed to visualize the trade-off between true positive and false positive rates. This suite of performance metrics aimed to thoroughly assess the transfer learning model's efficacy in enhancing fingerprint recognition. The inclusion of a Confusion Matrix ensured a comprehensive and nuanced evaluation, contributing to a thorough understanding of the model's capabilities and limitations.

Table 3 presents an insightful view of the performance metrics of the Xception and InceptionResNetV2 models at different numbers of epochs in the context of student fingerprint recognition. The results demonstrate consistently high scores across various metrics, reflecting the robustness and efficacy of both models in the given task.

At 20 epochs, the Xception model exhibits exceptional performance with an accuracy score of 99.81%, precision, recall, F1 score, and Matthews Correlation Coefficient (MCC) scores all above 99.79%. The InceptionResNetV2 model at 20 epochs surpasses these impressive results, achieving perfect scores of 100% across all metrics, highlighting its remarkable accuracy and reliability in student fingerprint recognition.

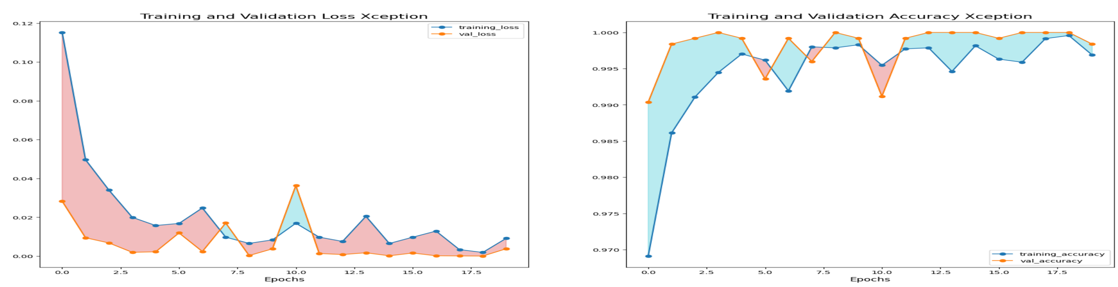
As the number of epochs increases to 30, both models maintain high-performance levels. The Xception model maintains strong scores, with only slight variations, showcasing its consistency in accurately identifying student fingerprints. Notably, the InceptionResNetV2 model sustains perfection across all metrics, emphasizing its stability and outstanding performance even with increased training epochs.

Table 3. Performance metric

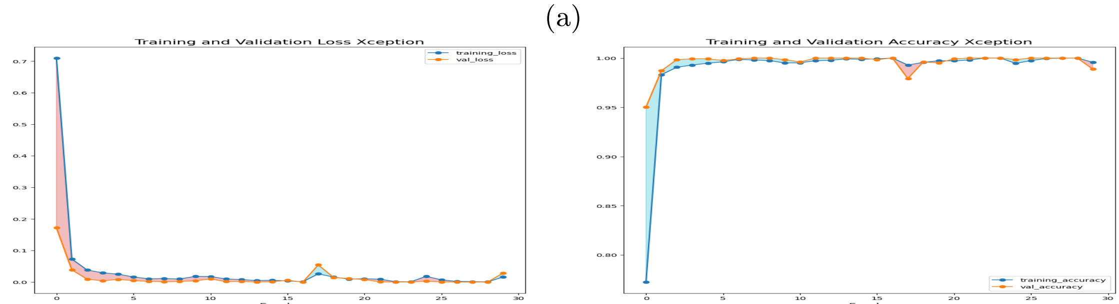
Model	Number of epochs	Accuracy Score (%)	Precision Score (%)	Recall Score (%)	F1 Score (%)	MCC (%)
Xception	20	99.81	99.81	99.81	99.81	99.79
InceptionResNetV2	20	100	100	100	100	100
Xception	30	99.13	99.15	99.13	99.13	99.04
InceptionResNetV2	30	100	100	100	100	100

4.2 Loss and accuracy

Figure 3 illustrates the assessment of loss and accuracy metrics for the Xception and InceptionResNetV2 models. It is evident from the data presented that the InceptionResNetV2 model outperforms its counterpart, demonstrating greater efficiency in comparison to the Xception model.



(a)



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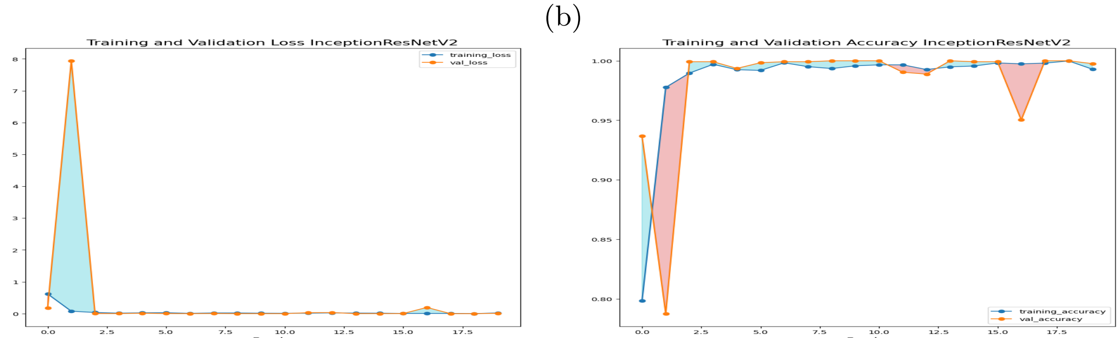

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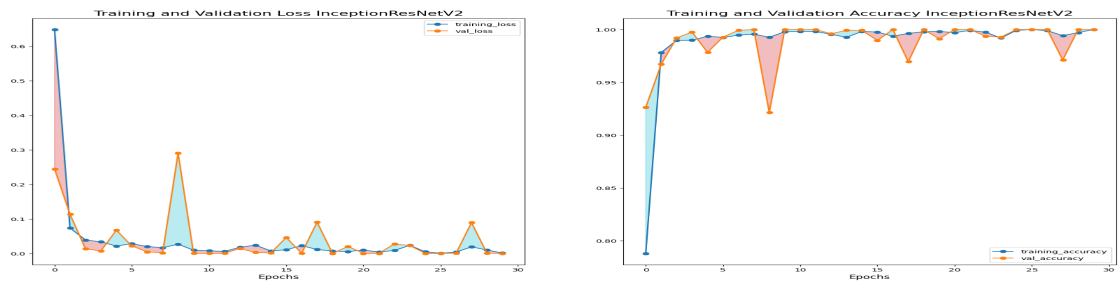


(d)

Fig. 3. Loss and accuracy of the experiment using (a) Xception with 20 epochs, (b) Xception with 30 epochs, (c) Inceptionresnetv2 with 20 epochs, and (d) Inceptionresnetv2 with 30 epochs.

4.3 Classification report

The classification reports for Xception and InceptionResNetV2 models at different epochs showcase exceptional performance in classifying individual students (Stu-dent00 to Student09). In Figure 4(a), Xception with 20 epochs achieves perfect precision, recall, and F1 scores of 100%, demonstrating remarkable accuracy in identifying student fingerprints. The overall dataset accuracy of 100% underscores the model's exceptional effectiveness on a broader scale. Figure 4(b) illustrates Xception with 30 epochs, maintaining consistently high precision, recall, and F1 scores (97% to 100%), with an impressive 99% overall accuracy. Figure 4(c) and Figure 4(d) depict InceptionResNetV2 at 20 and 30 epochs, respectively, achieving perfect scores of 100% for precision, recall, and F1, demonstrating exceptional accuracy in classifying student fingerprints. The overall accuracies of 100% in both cases underscore their remarkable effectiveness on a broader scale. The macro and weighted average metrics further affirm the models' outstanding capability to achieve precise and reliable classifications across a diverse set of students.

	precision	recall	f1-score	support
Student00	0.99	1.00	1.00	207
Student01	1.00	1.00	1.00	208
Student02	1.00	1.00	1.00	206
Student03	1.00	1.00	1.00	207
Student04	1.00	1.00	1.00	207
Student05	1.00	1.00	1.00	208
Student06	1.00	1.00	1.00	207
Student07	1.00	1.00	1.00	207
Student08	1.00	0.99	1.00	207
Student09	1.00	1.00	1.00	207
accuracy			1.00	2071
macro avg	1.00	1.00	1.00	2071
weighted avg	1.00	1.00	1.00	2071

(a)

	precision	recall	f1-score	support
Student00	0.98	1.00	0.99	207
Student01	1.00	1.00	1.00	208
Student02	0.98	1.00	0.99	206
Student03	1.00	1.00	1.00	207
Student04	0.97	1.00	0.98	207
Student05	1.00	1.00	1.00	208
Student06	0.99	1.00	0.99	207
Student07	1.00	0.97	0.98	207
Student08	1.00	1.00	1.00	207
Student09	1.00	0.97	0.98	207
accuracy			0.99	2071
macro avg	0.99	0.99	0.99	2071
weighted avg	0.99	0.99	0.99	2071

(b)

	precision	recall	f1-score	support
Student00	1.00	0.97	0.98	207
Student01	0.98	1.00	0.99	208
Student02	0.99	1.00	1.00	206
Student03	1.00	1.00	1.00	207
Student04	1.00	1.00	1.00	207
Student05	1.00	1.00	1.00	208
Student06	1.00	1.00	1.00	207
Student07	0.99	1.00	1.00	207
Student08	1.00	1.00	1.00	207
Student09	1.00	1.00	1.00	207
accuracy			1.00	2071
macro avg	1.00	1.00	1.00	2071
weighted avg	1.00	1.00	1.00	2071

(c)

	precision	recall	f1-score	support
Student00	1.00	1.00	1.00	207
Student01	1.00	1.00	1.00	208
Student02	1.00	1.00	1.00	206
Student03	1.00	1.00	1.00	207
Student04	1.00	1.00	1.00	207
Student05	1.00	1.00	1.00	208
Student06	1.00	1.00	1.00	207
Student07	1.00	1.00	1.00	207
Student08	1.00	1.00	1.00	207
Student09	1.00	1.00	1.00	207
accuracy			1.00	2071
macro avg	1.00	1.00	1.00	2071
weighted avg	1.00	1.00	1.00	2071

(d)

Fig. 4. Classification report of experiment (a) XCEPTION with 20 epochs, (b) XCEPTION with 30 epochs, (c) INCEPTIONRESNETV2 with 20 epochs, and (d) INCEPTIONRESNETV2 with 30 epochs.

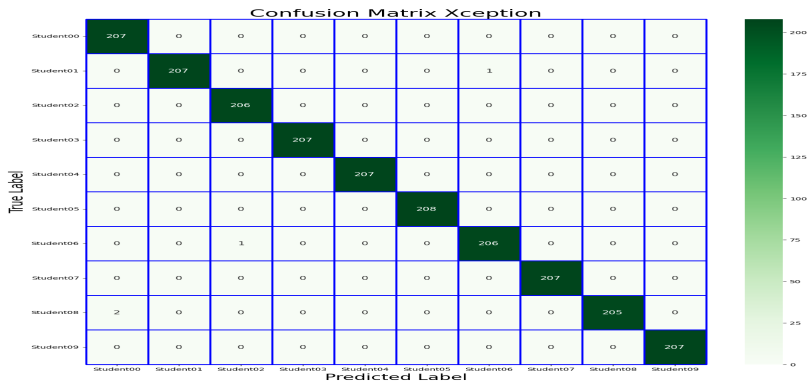
4.4 Confusion Matrix

The Confusion Matrix presented in Figure 5(a) provides a detailed breakdown of the model's predictions for each student (Student00 to Student09) using Xception with 20 epochs. Each row corresponds to the true labels, while each column represents the predicted labels. The diagonal elements indicate correct predictions, and off-diagonal elements represent misclassifications. Notably, the matrix reveals that the model achieved perfect predictions for most students, with 207 correct predictions out of 207 instances for Student00, Student03, Student04, Student07, and Student09. Additionally, there were 206 correct predictions out of 206 instances for Student02 and 208 correct predictions out of 208 instances for Student05. There are minor misclassifications for a few students, such as Student01, Student06, and Student08, where 1 or 2 instances were mispredicted.

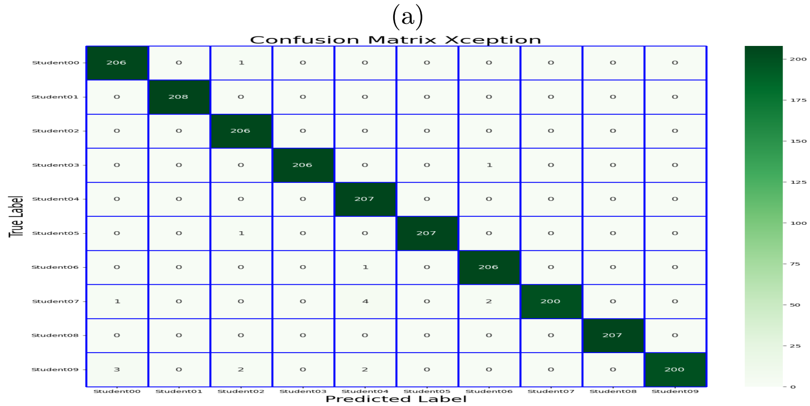
The Confusion Matrix depicted in Figure 5 (b) provides a comprehensive overview of the model's predictions for each student (Student00 to Student09) using Xception with 30 epochs. Each row corresponds to the true labels, while each column represents the predicted labels. The diagonal elements signify accurate predictions, while off-diagonal elements indicate misclassifications. Notably, the matrix reveals that the model achieved a substantial number of correct predictions for several students. However, there are instances of misclassifications, particularly for Student07 and Student09, where a few instances were inaccurately predicted.

The Confusion Matrix illustrated in Figure 5 (d) provides a detailed breakdown of InceptionResNetV2's predictions for each student (Student00 to Student09) after 30 epochs. Each row corresponds to the true labels, while each column represents the predicted labels. The diagonal elements indicate accurate predictions, and off-diagonal elements represent misclassifications. Remarkably, the matrix shows that the model achieved perfect predictions for all students, with 100% accuracy for each student. This signifies the model's exceptional accuracy in classifying student fingerprints, demonstrating its effectiveness across the entire dataset.

The Confusion Matrix depicted in Figure 5 (b) provides a detailed representation of the predictions made by InceptionResNetV2 after 20 epochs for each student (Student00 to Student09). Each row corresponds to the true labels, and each column represents the predicted labels. The diagonal elements signify correct predictions, while off-diagonal elements indicate misclassifications. Notably, there are a few instances of misclassifications, particularly for Student00, Student01, Student06, Stu-dent08, and Student09, where 1 to 5 instances were mispredicted. The inclusion of these misclassifications offers valuable insights into the model's performance, providing a nuanced view of its classification accuracy for each class.



(a)



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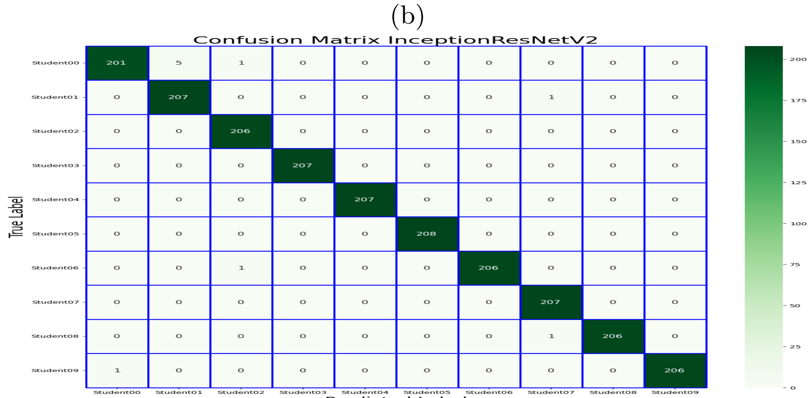

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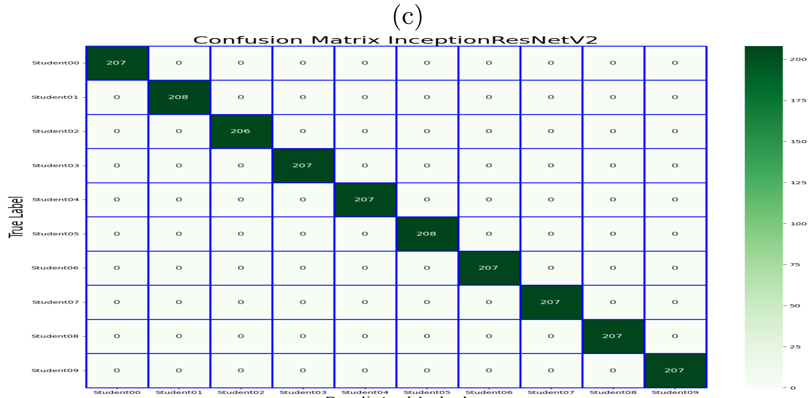
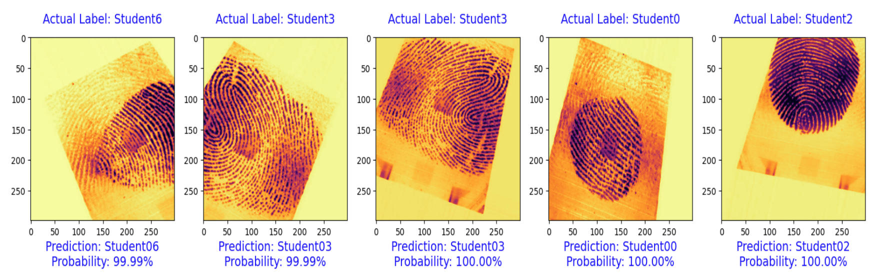


(d)

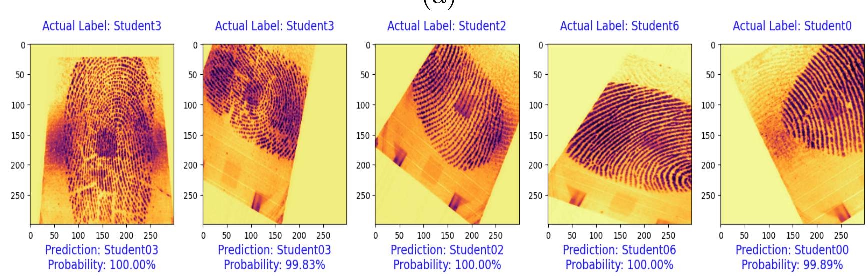
Fig. 5. The confusion matrix of the experiment (a) XCEPTION with 20 epochs, (b) XCEPTION with 30 epochs, (c) INCEPTIONRESNETV2 with 20 epochs, and (d) INCEPTIONRESNETV2 with 30 epochs.

4.5 Predictions of Xception and Inceptionresnetv2 models

The results of the test predictions for the pre-trained models, including Xception and InceptionResNetV2, are depicted in Figure 6. Each subfigure (a, b, c, and d) illustrates the performance of the respective model. The test predictions of Xception with 20 epochs exhibit notable accuracy, achieving a probability range of 99.97% to 100% for predicting student names corresponding to each actual label. Xception with 30 epochs, although slightly lower in probability, ranges between 93.86% and 100% for predicting student names corresponding to each actual label, respectively. InceptionresNetV2 with 20 epochs shows further improvement, with a probability range of 65.40% to 100% for predicting student names corresponding to each actual label. Finally, InceptionResNetV2 with 30 epochs emerges as the top-performing model, achieving the highest probability of 100% for predicting student names corresponding to each actual label. These findings highlight the effectiveness of InceptionResNetV2 in fingerprint recognition for student attendance.



(a)



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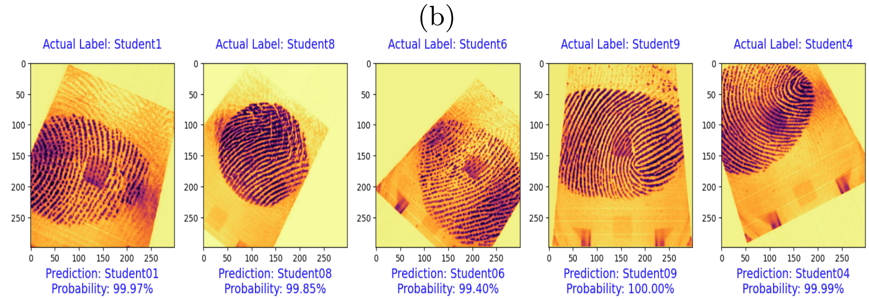

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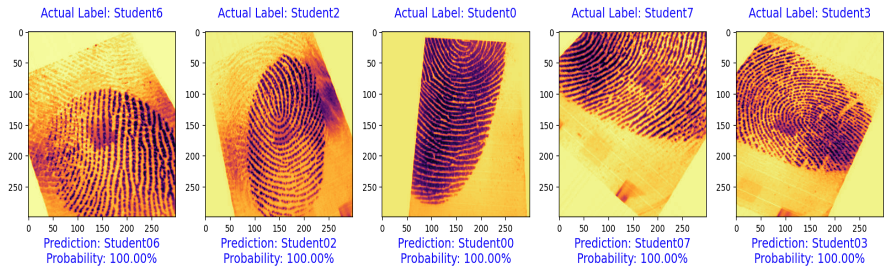

(d)

Fig. 6. Test predictions of experiment (a) XCEPTION with 20 epochs, (b) XCEPTION with 30 epochs, (c) INCEPTIONRESNETV2 with 20 epochs, and (d) INCEPTION-RESNETV2 with 30 epochs.

5 Comparative analysis

The comparative analysis of the Xception and InceptionResNetV2 models, trained on the CASIA Fingerprint v5.0 dataset, shows that both models perform exceedingly well in fingerprint recognition tasks, as presented in Table 4. Xception achieves an accuracy, precision, recall, and F1 score of around 99.81%, indicating a high level of performance in accurately and reliably identifying fingerprints. In contrast, InceptionResNetV2 achieves perfect scores of 100% across all metrics, suggesting it is exceptionally accurate in identifying all actual positive instances and ensuring that all positive predictions are correct. While Xception offers impressive results, InceptionResNetV2 stands out for scenarios where error minimization is paramount. The choice between these models should also consider factors such as computational demands and training efficiency, where Xception might be preferable due to its simpler architecture.

Table 4. Comparative analysis of the Xception and InceptionResNetV2

Model	Accuracy Score (%)	Precision Score (%)	Recall Score (%)	F1 Score (%)	MCC (%)
Xception	99.81	99.81	99.81	99.81	99.79
InceptionResNetV2	100	100	100	100	100

6 Conclusions

In conclusion, this study has presented substantial advancements and noteworthy findings. The incorporation of state-of-the-art architectures, namely Xception and InceptionResNetV2, coupled with transfer learning techniques, has demonstrated remarkable success in elevating the precision and dependability of fingerprint recognition for student attendance tracking. By leveraging pre-trained models, the system showcased a commendable ability to accurately identify and authenticate students based on their unique fingerprints.

Additionally, this research highlights the strategic use of data augmentation techniques to address the challenges associated with limited dataset sizes. This approach not only ensures the robustness of the proposed method but also enhances its generalizability and adaptability to diverse scenarios. The comprehensive evaluation of the proposed approach through various performance metrics, including Accuracy Score, Precision Score, Recall Score, F1 Score, and MCC, underscores its effectiveness in achieving superior results. The attained 100% accuracy rate in fingerprint recognition is a testament to the robustness and reliability of the transfer learning approach in the context of student attendance systems.

In a broader context, this study contributes significantly to the intersection of bio-metrics and educational technology. The findings have practical implications for the development of more advanced and accurate attendance-tracking systems in educational settings. The success of the transfer learning approach opens avenues for further research and development, encouraging the exploration of innovative methodologies to enhance various aspects of student-centric technological applications. Overall, the outcomes of this research mark a substantial step forward in leveraging transfer learning for the improvement of student attendance systems through cutting-edge fingerprint recognition techniques.

References

1. K. Alhanaee, M. Alhammadi, N. Almenhali, and M. Shatnawi, "Face recognition smart attendance system using deep transfer learning," in Procedia Computer Science, Elsevier B.V., 2021, pp. 4093–4102. https://doi.org/10.1016/j.procs.2021.09.184.
2. F. Zhuang et al., "A Comprehensive Survey on Transfer Learning," Nov. 2019, [Online]. Available http://arxiv.org/abs/1911.02685.
3. S. Ennajar and W. Bouarifi, "Deep Transfer Learning Approach for Student Attendance System During the COVID-19 Pandemic," J. Comput. Sci., vol. 20, no. 3, pp. 229–238, 2024, https://doi.org/10.3844/jcssp.2024.229.238.
4. F. Chollet, "Xception: Deep learning with depthwise separable convolutions," Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, vol. 2017-January, pp. 1800–1807, 2017, https://doi.org/10.1109/CVPR.2017.195.
5. C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-ResNet and the impact of residual connections on learning," 31st AAAI Conf. Artif. Intell. AAAI 2017, pp. 4278–4284, 2017, https://doi.org/10.1609/aaai.v31i1.11231.
6. T. N. Do and M. T. Tran-Nguyen, "Training Deep Network Models for Fingerprint Image Classification," Lect. Notes Networks Syst., vol. 363 LNNS, no. January, pp. 327–337, 2022, https://doi.org/10.1007/978-3-030-92666-3_28.
7. M. Alhothaily, M. Alradaey, M. Oqbah, and A. El-Kustaban, "Fingerprint Attendance System for Educational Institutes," J. Sci. Technol., vol. 20, no. 1, pp. 34–44, 2015, https://doi.org/10.20428/jst.20.1.4.
8. N. Z. Lamin, W. N. A. W. Jusoh, J. Zainudin, and H. Samad, "Implementing Student Attendance System Using Fingerprint Biometrics for Kolej Universiti Poly-Tech Mara," IOP Conf. Ser. Mater. Sci. Eng., vol. 1062, no. 1, 2021, https://doi.org/10.1088/1757-899X/1062/1/012037.

9. H. Walhazi, A. Maalej, and N. E. B. Amara, “A multi-classifier system for automatic fingerprint classification using transfer learning and majority voting,” Multimed. Tools Appl., vol. 83, no. 2, pp. 6113–6136, 2024, https://doi.org/10.1007/s11042-023-15337-6.
10. R. Kute, V. Vyas, and A. Anuse, “Transfer learning for face recognition using fingerprint biometrics,” J. King Saud Univ. - Eng. Sci., no. xxxx, 2021,https://doi.org/10.1016/j.jksues.2021.07.011.
11. P. Verma and N. Gupta, “Fingerprint Based Student Attendance System Using GSM,” Int. J. Sci. Res., vol. 2, no. 10, pp. 128–131, 2013, [Online]. Available www.ijsr.net.
12. A. I. Abdullateef, Ekwemuka, Itopa, Makinwa, and S. A. Alim, “Fingerprint Based Student Attendance Management System With Automatic Excel Computation,” LAUTECH J. Eng. Technol., vol. 12, no. 2, pp. 123–135, 2018, [Online]. Available:https://www.laujet.com/index.php/laujet/article/view/333.
13. L. S. Ezema, J. N. Eneh, and I. Amanze, “FINGERPRINT-BASED-ATTENDANCE-MANAGEMENT-SYSTEM,” Int. J. Sci. Eng. Res., vol. 6, no. 7, pp. 1623–1628, 2015.
14. CASIA Fingerprint Image Database.[Online]. Available: http://biometrics.idealtest.org/downloadDesc.do?id=7/.